

Year 4 — Approximations of Functions

Based on lectures by Prof. Nick Trefethen

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These notes are not endorsed by the lecturers, and I have modified them (often significantly) after lectures. They are nowhere near accurate representations of what was actually lectured, and in particular, all errors are almost surely mine (especially the typos!).

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1 Introduction - Approximation Theory

This is the foundation of constructive analysis and the foundation of numerical analysis. The subject is 150 years old with Chebyshev and has 5 eras,

Chebyshev Era, 1800 - 1899

This is in the 19th Century. Some names include, Jacobi, Chebyshev, Zolotarev, Weierstrass and Runge. The flavour were expansions and series (Taylor and Fourier), Orthogonal Polynomials and best approximations (approximations that are optimal in ∞ -norm).

Classical Era, 1900 - 1925

Some names include, Lebesgue, Bernstein, Jackson, De la Vallée Poussin, Faber, Fejér and Riesz. These are all names linked with analysis. These are the era of the foundation of analysis. We went from just formula and mapping from sets to sets. The approximation is how we bridge these ideas. This was all halted by the war.

Neoclassical Era, 1950-1975

This was the era of computers. This changed everything. Hence the field became into its own. Some names are, Davis, Cheney, Meinardes, Riblin, Lorentz, Rice, de Boor. These are people that have died very recently. Most of these people wrote great textbooks and created journals. They studied, splines, rational approximation.

Numerical Era, 1985 -

As time goes on, here we get proper computing. They studied, wavelets, radial basis functions, spectral methods, hp-finite element methods, chebfun.

High-Dimensional Era, 2010 -

Compressed Sensing, randomised algorithms, data science, deep learning, low rank approximation.

2 Chebyshev Points and Interpolants

Chebyshev is the same as Fourier, but not for periodic functions. Let $n \geq 0$ and P_n is the set of polynomials of degree n ($\leq n$). Let $\{x_0, \dots, x_n\}$ be $n + 1$ distinct points in $[-1, 1]$. Suppose we have $\{f_0, \dots, f_n\}$ a set of \mathbb{R} or \mathbb{C} numbers. We know,

Claim. There exists a unique interpolant $p \in P_n$ to $\{f_i\}$ in $\{x_i\}$.

This is true for arbitrary points. But we will use Chebyshev points. That is,

$$x_j = \cos\left(\frac{j\pi}{n}\right) \quad 0 \leq j \leq n$$

and so Chebyshev points are projections of the unit circle. They get denser towards the edge of the unit. That is important because interpolants on these points go well. In `chebfun`, these are `chebpts(n+1)`. The contrast to Chebyshev points are equally spaced points, which are awful for interpolation. When we speak of a Chebyshev interpolant, we mean a unique polynomial that interpolates some data on the amount of Chebyshev points.

2.1 Clustering

This is what makes these points so good. The clustering has a beautiful property. Think of the Chebyshev points as electrons, they will find the minimal energy configuration. This is what Chebyshev points are. Take a point, then the geometric mean distance from any point to the others is approximately a half.

3 Fourier, Laurent, Chebyshev

Fourier, Laurent and Chebyshev are three equivalent ways of doing things. Each one is useful in their own area, they all have their different areas.

3.1 Fourier Analysis

- We have some $\theta \in [-\pi, \pi]$.
- $F(\theta)$ with $F(\theta) = F(-\theta)$.
- Analytic in a strip.
- For interpolation, we need $2n$ equispaced points.
- Trigonometric (Fourier) Polynomial,

$$\frac{1}{2} \sum_{k=1}^n a_k (e^{i\theta k} + e^{-i\theta k})$$

- Fourier Series,

$$\frac{1}{2} \sum_{k=1}^{\infty} a_k (e^{i\theta k} + e^{-i\theta k})$$

3.2 Laurent Analysis

- We have some $z \in D(0, 1)$, where $z = e^{i\theta}$.
- $\mathbb{F}(z)$ with $\mathbb{F}(z) = \mathbb{F}(z^{-1})$.
- Analytic in some annulus
- For interpolation, we need $2n$ roots of unity.
- Laurent Polynomial,

$$\frac{1}{2} \sum_{k=0}^n a_k (z^k + z^{-k})$$

- Laurent Series,

$$\frac{1}{2} \sum_{k=0}^{\infty} a_k (z^k + z^{-k})$$

3.3 Chebyshev Analysis

- We have some $x \in [-1, 1]$ where $x = \cos\theta = \frac{1}{2}(z + z^{-1})$.
- We have some $f(x)$ not restriction.
- Analytic in an ellipse (Bernstein Ellipse, which means focus at ± 1).
- For interpolation, we need $n + 1$ Chebyshev points.
- Polynomial,

$$\sum_{k=0}^n a_k T_k(x)^1$$

¹ $T_k(x)$ is the degree k Chebyshev polynomial

- Chebyshev Series,

$$\sum_{k=0}^{\infty} a_k T_k(x)$$

3.4 Chebyshev Series

3.4.1 Chebyshev Polynomials

It all comes from $z = e^{i\theta}$, which then says $z^k = e^{ik\theta}$ and $x = \frac{1}{2}(z + z^{-1}) = \cos\theta$. Then we define, $T_k(x) = \frac{1}{2}(z^k + z^{-k}) = \cos k\theta$. Another way to spell that out is, $T_k(x) = \cos(k \arccos(x))$.

Here is some examples,

$$T_0(x) = 1 \quad T_1(x) = x \quad T_2(x) = 2x^2 - 1 \quad T_3(x) = 4x^3 - 3x \quad T_4(x) = 8x^4 - 8x^2 + 1$$

and from this we can write the three term recurrence,

$$T_{k+1} = 2xT_k(x) - T_{k-1}(x) \quad k \geq 1$$

To derive this, we note that

$$\begin{aligned} T_{k+1}(x) &= \frac{1}{2}(z^{k+1} + z^{-k-1}) \\ &= \frac{1}{2}(z^k + z^{-k})(z + z^{-1}) - \frac{1}{2}(z^{k-1} + z^{1-k}) \\ &= 2xT_k(x) - T_{k-1}(x) \end{aligned}$$

One last note is that these are Orthogonal polynomials.

Theorem 3.1. If f is Lipschitz continuous on $[-1, 1]$, it has a unique representation as a Chebyshev series,

$$f(x) = \sum_{k=0}^{\infty} a_k T_k(x)$$

and this sum is absolutely and uniformly convergent. The coefficients a_k are given by,

$$a_k = \frac{2}{\pi} \int_{-1}^1 \frac{f(x)T_k(x)}{\sqrt{1-x^2}} dx \quad (k \geq 1)$$

and for $k = 0$,

$$a_0 = \frac{1}{\pi} \int_{-1}^1 \frac{f(x)}{\sqrt{1-x^2}} dx$$

Proof. Transplant to z or θ and use integrals. This is in the text. □

Example (Exercise 3.6). It happens,

$$|x| = \sum_{k=0}^{\infty} a_k T_k(x)$$

where,

$$a_k = \begin{cases} a_k = 0 & k = 2n + 1 \\ a_k = \frac{4(-1)^n}{(2^n - 1)\pi} & \end{cases}$$

Example (Exercise 3.15). What about e^x ? We find, $a_0 = I_0(1)$ and then, $a_k = 2I_k(1)$ for $k \geq 1$.

How chebfun resolves a function

- Sample on grids of size, 17, 33, 65, 129,
- On each grid, find coefficients c_k of chebshev, interpolants (via FFT),
- Stop when coefficients reach machine precision,
- Trim the series to some degree n .

4 Interpolants, Projections and Aliasing

Our setting is we are given some f that is Lipschitz continuous on $[-1, 1]$ and given some $n \geq 0$. There are two main ways to approximate f by a polynomial.

$$p_n(x) = \sum_{k=0}^n x_k T_k(x),$$

the Chebyshev interpolant, (we have already talked this), and,

$$f_n(x) = \sum_{k=0}^n a_k x_k T_k(x)$$

here we take the infinite series and then truncate it at n . This is the Chebyshev projection or truncation. The interpolant is natural for computation because it's a finite problem, while the truncation results in integrals and hence is infinite. We also call the interpolant 'by values' and the projection 'by projection'. We are going to see how c_k relate to a_k and they are basically the same.

4.1 Aliasing

Theorem 4.1. For any $n \geq 1$ and any $0 \leq m \leq n$ the following Chebyshev polynomials take the same values on the $(n+1)$ point Chebyshev grid,

$$T_m, \quad T_{2n-m}, \quad T_{2n+m}, \quad T_{4n-m}, \quad T_{4n+m}, \quad T_{6n-m}, \dots$$

Proof. Transplant to z . These polynomials are just $\frac{1}{2}$ times,

$$z^m + z^{-m}, \quad z^{2n-m} + z^{m-2n}, \quad z^{2n+m} + z^{-2n-m}, \dots$$

and further, $z^{2n} = 1$ on the $2n^{th}$ roots of unity and these are just the Chebyshev points. So all these are the same at the roots of unity of 1 and that implies all the Chebyshev polynomials are the same at the Chebyshev points. \square

Theorem 4.1 implies,

Theorem 4.2. If f is Lipschitz continuous on $[-1, 1]$, then $c_0 = a_0 + a_{2n} + a_{4n} + \dots$ and $c_n = a_n + a_{3n} + a_{5n} + \dots$ and for $0 < k < n$,

$$\begin{aligned} c_k &= a_k + a_{k+2n} + a_{k+2n} + \dots \\ &\quad + a_{-k+2n} + a_{-k+4n} + \dots \end{aligned}$$

Proof. If f is Lipschitz, then the Chebyshev series converges absolutely. Therefore, all of the above series converge, hence they define some degree n polynomial, $q \in \mathcal{P}_n$. At a gridpoint x_j we write,

$$f(x_j) = \sum_{k=0}^{\infty} a_k T_k(x_j) \quad q(x_j) = \sum_{k=0}^n c_k T_k(x_j)$$

At x_j these are the same numbers in different order! (Note Thm 4.1). Therefore $f(x_j) = q(x_j)$ for all x_j . Therefore q is indeed the Chebyshev interpolant p . \square

Corollary 4.3. The difference between f and f_n is,

$$f(x) - f_n(x) = \sum_{k=n+1}^{\infty} a_k T_k(x),$$

and the difference between p_n and f is,

$$f(x) - p_n(x) = \sum_{k=n+1}^{\infty} a_k(T_k(x) - T_m(x)),$$

where $m = |(k + n - 1)(\bmod 2n) - (n - 1)|$

5 Barycentric Interpolation Formula

Theorem 5.1 (Theorem 5.2 (Salzer 1972)). The degree n Chebyshev interpolant to data f_0, \dots, f_n is given by,

$$p(x) = \frac{\sum_{j=0}^n '(-1)^j f(j)/(x - x_j)}{\sum_{j=0}^n '(-1)^j /x - x_j}$$

we note \sum' means we multiply the $j = 0, n$ by a half. Further if $x = x_j$, then $p(x) = f_j$.²

What's the point? Well theres two good ways to compute polynomial interpolants,

- By points, this is via the Barycentric Interpolation Formula. If we want to evaluate a interpolant at a point, we have $o(n)$.
- By coeffs, for this we calculate $\{c_k\}$ via FFT, then we use the series. If we want to evaluate a interpolant at a point, we have $o(n \log(n))$.

We now look to a better formula,

Theorem 5.2 (Theorem 5.1 (Dupuy 1948)). The degree n interpolant x_0, \dots, x_n is,

$$p(x) = \frac{\sum_{j=0}^n \frac{\lambda_j f_j}{x - x_j}}{\sum_{j=0}^n \frac{\lambda_j}{x - x_j}} \quad (*)$$

where, $\lambda_j = \frac{1}{\prod_{k \neq j} (x_j - x_k)}$ is the barycentric weight.

Note. We regard $|\lambda_j| = \frac{1}{(\text{geometric mean distance of } x_j \text{ to the other points})^n}$

Proof. We note that $*$ is in Lagrange form (the sum of $n + 1$ functions),

$$p(x) = \sum_{j=0}^n f_j \ell_j(x)$$

where

$$\ell_j(x) = \frac{\frac{\lambda_j}{x - x_j}}{\sum_{k=0}^n \frac{\lambda_k}{x - x_k}}$$

This is a sum of cardinal functions³. We have to show this does what we expect, that is again, that $\ell_j(x) \in \mathcal{P}_n$ and

$$\ell_j(x_k) = \begin{cases} 1 & k = j \\ 0 & k \neq j \end{cases}.$$

Now for the juicy derivation. We know (we probably don't), the lagrange interpolant,

$$\ell_j(x) = \frac{\prod_{k \neq j} (x - x_k)}{\prod_{k \neq j} x_j - x_k}.$$

We define the node polynomial,

$$\ell(x) = \prod_{k=0}^n (x - x_k).$$

²Nick Higham proved this was numerically stable (Special Topic?)

³a cardinal (or Lagrange) function is a function that is zero at all the grid points except one.

Then,

$$\begin{aligned}\ell_j(x) &= \frac{\ell(x)}{(x - x_j) \prod_{j \neq k} (x_j - x_k)} \\ &= \frac{\ell(x) \lambda_i}{x - x_j}.\end{aligned}$$

Why is this the same as what we wrote before? Well just divide by one! Isn't this so trivial! The reason we do this is because,

$$1 = \sum_{k=0}^n \ell_k(x).$$

We find,

$$\ell_j(x) = \frac{\ell(x) \frac{\lambda_j}{x - x_j}}{\ell(x) \sum_{k=0}^n \frac{\lambda_k}{x - x_k}} = \frac{\frac{\lambda_j}{x - x_j}}{\sum_{k=0}^n \frac{\lambda_k}{x - x_k}}.$$

□

6 Convergence for differentiable functions

We look at the central dogma of approximation theory. We talk about the smoothness of f and that this corresponds to the rate of approximation of f . In this section we are going to consider f has several derivatives and we will see that this relates to algebraic convergence, and in the next section we are going to see that if f is analytic then we have exponential convergence.

In classical approximation theory we usually take a conservative view on approximation, but we can do better. We will consider the variation of a function.

Definition 6.1 (Variation). We define the variation of a function, f , on $[a, b]$ is,

$$\mathcal{V}(f) = \sup \sum |f(x_{i+1}) - f(x_i)|$$

for $a \leq x_1 < \dots < x_n \leq b$.

If $\mathcal{V}(f) < \infty$, then we say that f has bounded variation, $f \in \text{BV}$. We also can think about f as the one-norm of the derivative. That is,

$$\mathcal{V}(f) = \int_a^b |f'(x)| dx = \|f'\|_1$$

This holds if f has a continuous derivative. We can extend these ideas to non-continuous functions via Stieltjes Integration.

Example. • Let $f(x) = |x|$, then $\mathcal{V}(f) = \|f'\|_1 = 2$.

• Let $f(x) = \text{sgn}(x)$, then $\mathcal{V}(f) = 2$.

We shall assume that for some $\nu \in \mathbb{Z}_{\geq 0}$, $f, f', \dots, f^{(\nu-1)}$ are continuous and $f^{(\nu)}$ has $\mathcal{V}(f^{(\nu)}) < \infty$. We can now derive some theorems from this,

Theorem 6.2. Assume $\mathcal{V}(f^{(\nu)}) < \infty$ for some $\nu \geq 0$. Then,

$$|a_k| \leq \frac{2\mathcal{V}(f^{(\nu)})}{\pi(k-\nu)^{\nu+1}} \quad k \geq \nu + 1$$

This is saying we decrease and the approximations converge by $\mathcal{O}(k^{-\nu-1})$.

Idea (Too fiddly) Prof. Süli did it. Instead of doing the Chebyshev idea, we shall look at the Fourier analogue. Integration by parts. Given some 2π -periodic function $F(\theta)$ and suppose $\mathcal{V}(f^{(\nu)}) < \infty$. We now see,

$$F(\theta) = \sum_{k=-\infty}^{\infty} a_k e^{ik\theta}, \quad a_k = \frac{1}{2\pi} \int_{-\pi}^{\pi} F(\theta) e^{-ik\theta} d\theta$$

and look at the coefficients,

$$\begin{aligned} a_k &= \frac{1}{2\pi} \int_{-\pi}^{\pi} F(\theta) e^{-ik\theta} d\theta \\ &= \frac{1}{2\pi} \int_{-\pi}^{\pi} \frac{F'(\theta) e^{-ik\theta}}{ik} d\theta \\ &= \vdots \\ &= \frac{1}{2\pi} \int_{-\pi}^{\pi} \frac{F^{(\nu+1)}(\theta) e^{-ik\theta}}{(ik)^{\nu+1}} d\theta \end{aligned}$$

□

From the work in previous chapters, we can now say,

Theorem 6.3. Assume that $\nu \geq 1$. Then,

$$\|f - f_n\| \leq \frac{2\mathcal{V}(f^{(\nu)})}{\pi\nu(n-\nu)^\nu} \quad \mathcal{O}(n^{-\nu})$$

and,

$$\|f - p_n\| \leq \frac{4\mathcal{V}(f^{(\nu)})}{\pi\nu(n-\nu)^\nu} \quad \mathcal{O}(n^{-\nu})$$

Proof. We know,

$$\begin{aligned} f - f_n &= a_{n+1}T_{n+1} + a_{n+2}T_{n+2} + \dots \quad \|T_k\| = 1 \\ \|f - f_n\|_\infty &\leq \sum_{n+1}^{\infty} |a_k| \\ &\leq \frac{2\mathcal{V}(f^{(\nu)})}{\pi} \sum_{n+1}^{\infty} \frac{1}{(k-\nu)^{\nu+1}} \\ &\leq \frac{2\mathcal{V}}{\pi} \int_n^{\infty} \frac{ds}{(s-\nu)^{\nu+1}} \\ &= \frac{2\mathcal{V}}{\pi\nu(n-\nu)^\nu} \end{aligned}$$

and similarly for $\|f - p_n\|$, there is just an extra constant. \square

Example. Consider $f(x) = \text{sgn}(x)$, then we have $a_k = \mathcal{O}(k^{-1})$ and so we have $\|f - p_n\| = \mathcal{O}(1)$. Hence we can't approximate this nicely.

If $f(x) = |x|$, then $a_k = \mathcal{O}(k^{-2})$ and so $\|f - p_n\| = \mathcal{O}(n^{-1})$.

If $f(x) = |x|^3$, then $a_k = \mathcal{O}(k^{-4})$ and so $\|f - p_n\| = \mathcal{O}(n^{-3})$

7 Convergence for Analytic Functions

Assume we have f which is analytic in E_ρ for some $\rho > 1$ and also assume that $|f(x)| \leq M$ in E_ρ .

Theorem 7.1 (Bernstein).

$$|a_k| \leq 2M\rho^{-k} \quad \forall k \geq 0$$

Proof. Let $f(x) = F(z) = F(z^{-1})$. That is, $F(z) = f(1/2(z + z^{-1}))$, composition of two analytic functions, hence analytic. We know,

$$\begin{aligned} f(x) &= \sum_{k=0}^{\infty} a_k T_k(x) \\ F(z) &= \frac{1}{2} \sum_{k=0}^{\infty} a_k (z^k + z^{-k}) \end{aligned}$$

are the same, where,

$$a_k = \frac{1}{\pi i} \int_{|z|=1} z^{-1-k} F(z) dz$$

but this can be the same as, for $s < \rho$,

$$a_k = \frac{1}{\pi i} \int_{|z|=s} z^{-1-k} F(z) dz$$

and so this implies,

$$|a_k| \leq \frac{1}{\pi} s^{-1-k} M 2\pi s = 2Ms^{-k}$$

and hence,

$$|a_k| \leq 2M\rho^{-k}.$$

□

From this, the following theorem follows,

Theorem 7.2.

$$\|f - f_n\| \leq \frac{2M\rho^{-n}}{\rho - 1}$$

and,

$$\|f - p_n\| \leq \frac{4M\rho^{-n}}{\rho - 1}$$

Proof. We know,

$$\begin{aligned} f - f_n &= a_{n+1}T_{n+1} + a_{n+2}T_{n+2} + \dots \\ \|f - f_n\| &\leq \sum_{k=n+1}^{\infty} |a_k| \\ &\leq 2M \sum_{k=n+1}^{\infty} \rho^{-k} \\ &= \frac{2M\rho^{-n-1}}{1 - 1/\rho} = \frac{2M\rho^{-n}}{\rho - 1} \end{aligned}$$

Similarly, for $f - p_n$.

□

Here is a converse to the first result,

Theorem 7.3. Suppose f on $[1, -1]$ has approximations q_n such that $\|q - q_n\| \leq C\rho^{-n}$ for some $p > 1$. Then f is analytic in E_ρ .

Proof. This is based on $f = q_0 + (q_1 - q_0) + (q_2 - q_1) + \dots$ and the exponential convergence implies these are small and the result follows from this. \square

How close is a point to the unit interval as measured by these ellipses. For two singularities, one at the minor axis and one at the major, then we need the changes to be $\varepsilon \approx \sqrt{2\delta}$, where ε is the distance on the minor axis and δ at the major axis.

8 Gibbs Phenomenon

What is it? Algebraic overshoots near jumps. There are three cases,

- Interpolation, with a jump midway between grid points. We get a 28.2% overshoot.
- Interpolation, with a jump at a point. We get a 6.6% overshoot.
- Projection. We get a 17.9% overshoot.

The real reason we don't like this, is that we don't approximate functions with jumps with polynomials. These are bad polynomials to approximate. There is an aspect here, the decay rate away from a singularity. It is inverse linear decay away, this is very bad. Polynomials: error decay, $\mathcal{O}(\frac{1}{x})$ away from jump. This is algebraic and slow. However, splines are piecewise polynomials, and they have error decay this is exponential!

9 Best Approximation

We call the best approximation of $p^* \in \mathcal{P}$ such that $\|f - p^*\|$ is minimum. We can observe that there is ‘equioscillation’ in greater than $n+2$ points and ‘alternant’ of exactly $n+2$ points where the error ‘equioscillates’. The ‘error curve’ is the difference $(f - p)([-1, 1])$. Then we have a theorem,

Theorem 9.1 ((1902. Kirchberger)). Given f is an arbitrary continuous function on the unit interval, real, and given $n \geq 0$, there exists a unique best approximation to f , $p^* \in \mathcal{P}_n$, characterised by equioscillation between at least $n+2$ extremum.

Proof. Proof in four parts. We will show existence, equioscillation implies optimality, optimality implies equioscillation and uniqueness. Firstly **existence**. Let $p \in \mathcal{P}_n$ be defined by its $n+1$ coefficients. Then, $\|f - p\|_2$ is a continuous function of p . If p^* exists, it lies in $\{p \in \mathcal{P}_n : \|f - p\| \leq \|f - 0\|\}$. This is a closed, bounded subset of \mathbb{R}^{n+1} , hence compact. So the minimum is attained.

Now we want to show **equioscillation implies optimality**. Suppose we have $f - p$ equioscillates between $n+2$ extrema, but suppose it isn’t optimal. That is, $\|f - (p + q)\| \leq \|f - p\|$ for some $q \in \mathcal{P}_n$. Then draw a picture. We count the zeros. q has alternating signs at least $n+2$ points. Hence q has at least $n+1$ zeros. Hence $q = 0$, contradiction.

Optimality implies equioscillation. Suppose the contrary. Suppose $p \in \mathcal{P}$ such that $f - p$ equioscillates at only $k+1 \leq n+1$ points (too few!). Now draw a picture. Draw some lines between these points between the alternating extrema. Let these lines be x_1, x_2, \dots, x_k . Define $q(x) = (x - x_1)(x - x_2) \dots (x - x_k) \in \mathcal{P}_k \subseteq \mathcal{P}_n$. Then $\|f - (p + \varepsilon q)\| < \|f - p\|$ for all sufficiently small epsilon of the right sign.

Uniqueness. Suppose p and q are both best approximations to f . Then $r = (p + q)/2$ is also a best approximation. So r must have at least $n+2$ equioscillation extrema. We notice that p and q must take the same values at the at least $n+2$ extrema. Hence $p = q$. \square

9.1 Calculating p^*

Suppose f and n are given. Now we want to compute p^* . This is a non-linear problem, hence it must iterate. This is the Remez algorithm in the 1930s in Kyiv. The idea is pick a set of points, a trial alternant $n+2$ points. Then we interpolate and then adjust the points iteratively⁴.

⁴M.J.D Powell Book

10 Hermite Integral Formula

We firstly review residue calculus. We know that,

$$\oint_{\Gamma} g(z)dz = \sum \text{resg}(z)$$

If g has a simple pole at a point z_0 , the residue is,

$$\text{res} = \lim_{z \rightarrow z_0} (z - z_0)g(z).$$

Suppose that $g = 1/h(z)$ and h has a simple zero at z_0 . Then,

$$\text{res} = \lim_{z \rightarrow z_0} \frac{z - z_0}{h(z)} = \frac{1}{h'(z_0)}.$$

That concludes the review of residue calculus.

Let f be analytic on and inside Γ , enclosing $[-1, 1]$ and let $x_0, \dots, x_n \in [-1, 1]$ be distinct. We let p_n to be the degree n interpolant to f in $\{x_k\}$. We recall the node polynomial,

$$\ell(x) = \pi_{k=0}^n (x - x_k).$$

Theorem 10.1. We have the following formulae,

$$p(x) = \frac{1}{2\pi i} \oint_{\Gamma} \frac{\ell(t) - \ell(x)}{\ell(t)} \frac{f(t)}{t - x} dt$$

and the error,

$$f - p(x) = \frac{1}{2\pi i} \oint_{\Gamma} \frac{\ell(x)}{\ell(t)} \frac{f(t)}{t - x} dt$$

Where does the power come from? Well from $\frac{\ell(x)}{\ell(t)}$. If we have x close to the interpolation point and t is far away on the contour, then we have $\frac{\ell(x)}{\ell(t)}$ is exponentially small as $n \rightarrow \infty$ if f is analytic in a big region.

Proof. We shall consider,

$$\frac{1}{2\pi i} \oint_{\Gamma_j} \frac{\ell(x)}{\ell(t)(x - t)} dt$$

and define Γ_j as the contour that encloses x_j but no other x_k or x . The integrand has a simple pole at $t = x_j$, with residue,

$$\frac{\ell(x)}{\ell'(x_j)(x - x_j)}.$$

This is the cardinal polynomial, ℓ_j . Now we enlarge Γ_j (Γ') to enclose all of the x_0, \dots, x_n but still not x . We get,

$$p(x) = \frac{1}{2\pi i} \oint_{\Gamma'} \frac{\ell(x)f(t)}{\ell(t)(x - t)} dt.$$

Now enlarge Γ' to Γ , enclosing x . We then get,

$$p(x) - f(x) = \frac{1}{2\pi i} \oint_{\Gamma} \frac{\ell(x)f(t)}{\ell(t)(x - t)} dt$$

because now we enclose one more pole at $t = x$, with residue $-f(x)$. This is the second equation in the result. For the rest of the result we need to show that,

$$f(x) = \frac{1}{2\pi i} \oint_{\Gamma} \frac{\ell(t)}{\ell(t)} \frac{f(t)}{t - x} dx,$$

and this is true by residue calculus. □

11 Discussion of high-degree interpolation

There is some historical confusion here. There are two big theorems here, we have talked about Runge's Theorem, but not Faber's Theorem.

Theorem 11.1 (Faber, 1914). There does not exist any family of grids for interpolation in which polynomial interpolants converge for all continuous $f \in C([-1, 1])$.

and Runge showed,

Theorem 11.2 (Runge, 1901). Polynomials in equally spaced grids may diverge exponentially, even if f is analytic.

These results made interpolation seem like an awful idea. These explanations are really off piece. The flaw in Faber, is that most functions are smoother than $([-1, 1])!$ For Runge, the point is not to use equally spaced points, Chebyshev points are great. Here two factors combine,

- **Conditioning of the problem**, the interpolation of equally spaced points is exponentially ill-conditioned.
- **Stability of the algorithms**, we have seen polyval and polyfit. These are unstable, exponentially unstable.

(*Proof of Faber's Theorem*). We define $L_n : f \mapsto p_n$. Suppose $L_n f \rightarrow f$ as $n \rightarrow \infty$ for all continuous functions $f \in C([-1, 1])$. Since $([-1, 1])$ is a Banach space, it follows from the uniform boundedness principal that, $\{\|L_n\|\}$ are bounded, but by Theorem 15.2,

$$\|L_n\| \geq \frac{2}{\pi} \ln(n+1) \rightarrow \infty$$

□

For a historical note, we note that Faber and Bernstein used the bound,

$$\|L_n\| \geq \frac{1}{12} \ln(n)$$

12 Lebesgue Constants

Imagine we have polynomial interpolation in distinct $x_0, \dots, x_n \in [-1, 1]$. Then we can,

$$p(x) = \sum_{j=0}^n \ell_j(x) f_j \quad f_j = f(x_j), f \in [-1, 1].$$

Then the Lebesgue constant, Λ ,

$$\Lambda = \sup_f \frac{\|p\|}{\|f\|}.$$

We see that Λ is just the infinity norm of the interpolation operator. We can compute it in such a simple way. It is equal to the maximum possible size of p , if all the data are at most $|f_j| \leq 1$. The Lebesgue function, λ ,

$$\lambda(x) = \sup_f \frac{|p(x)|}{\|f\|} = \sum_{j=0}^n |\ell_j(x)|,$$

and so we have the simple formula of,

$$\Lambda = \sup_{x \in [-1, 1]} \lambda(x).$$

Theorem 12.1. We interpolate f , then,

$$\|f - p\| \leq (\Lambda + 1) \|f - p^*\|,$$

that is, if Λ is small then polynomial interpolants are near best.

Proof. We note that p is the interpolant to f . So, $p - p^*$ is the interpolant to $f - p^*$. We compute the error,

$$\begin{aligned} \|f - p\| &\leq \|f - p^*\| + \|p - p^*\| \\ &\leq \|f - p^*\| + \Lambda \|f - p^*\| \\ &= (\Lambda + 1) \|f - p^*\|. \end{aligned}$$

□

Theorem 12.2. Chebyshev points, it is known,

$$\begin{aligned} \Lambda_n &\sim \frac{2}{\pi} \log(n) \quad n \rightarrow \infty \\ \Lambda_n &\leq \frac{2}{\pi} \log(n+1) + 1 \quad n \geq 0 \end{aligned}$$

Optimal points (no good) (minimise the Lebesgue constant),

$$\begin{aligned} \Lambda_n &\sim \frac{2}{\pi} \log(n) \quad n \rightarrow \infty \\ \Lambda_n &\geq \frac{2}{\pi} \log(n+1) + 0.52125... \quad n \geq 0 \end{aligned}$$

Equally spaced points

$$\begin{aligned} \Lambda_n &\sim \frac{2^{n+1}}{en \log(n)} \quad n \rightarrow \infty \\ \Lambda_n &\geq \frac{2^{n-2}}{n^2} \quad n \geq 1 \end{aligned}$$